Applying improved median linkage heuristic for cell formation problem considering binary data

Tamal Ghosh* and Pranab K. Dan

Department of Industrial Engineering and Management,
West Bengal University of Technology,
BF 142, Salt Lake City, Kolkata 700064, India
E-mail: tamal.31@gmail.com
E-mail: danpk.wbut@gmail.com
*Corresponding author

Abstract: The crucial problem in cellular manufacturing system (CMS) is to identify the machine cells and corresponding part families to form the production cells. This article portrays a novel approach based on median linkage clustering (MLC) algorithm to form the production cells. The projected technique is demonstrated in two portions. Firstly, the MLC procedure and Nei and Li's similarity coefficient method are incorporated to obtain the machine cells. Thereafter, a modified part assignment technique is recommended to form the corresponding part-families. The proposed technique is shown to outperform the other published methodologies and produced improved solutions for the test datasets.

Keywords: cell formation; CF; median linkage algorithm; cluster analysis; heuristic; cellular manufacturing modelling.

Reference to this paper should be made as follows: Ghosh, T. and Dan, P.K. (xxxx) 'Applying improved median linkage heuristic for cell formation problem considering binary data', *Int. J. Modelling in Operations Management*, Vol. X, No. Y, pp.000–000.

Biographical notes: Tamal Ghosh is a graduate student in the Department of Industrial Engineering and Management, West Bengal University of Technology, India. He has also obtained his Bachelor of Technology (BTech) in Computer Science and Engineering from National Institute of Technology Calicut, India. His current research area is the application of soft computing techniques in cellular manufacturing. He has number of articles published in international journals and conferences.

Pranab K. Dan is a Reader in the Department of Industrial Engineering and Management, West Bengal University of Technology, India. He has obtained his PhD in Production Engineering in 1996 from Jadavpur University, India. He has obtained his Bachelor of Engineering and Master of Engineering in Mechanical Engineering from Bengal Engineering College, Shibpore affiliated to Calcutta University, India in the year 1980 and 1982, respectively. His research and professional experience is in the area of industrial engineering. He has number of articles published in international journals and conferences.

1 Introduction

Traditionally in cellular manufacturing systems (CMS), group technology (GT) could be stated as a manufacturing metaphysics which recognises similar parts. The objective is to group them into several part families depending on their manufacturing designs, features and geometric shapes which was first proposed by Burbidge (1963). GT is utilised in CMS to obtain an alternative of traditional manufacturing system. Designing production cell has been called cell formation problem (CF/CFP), consists of the following procedures: usually homogeneous parts are grouped into part families following their processing requirements and dissimilar machines are grouped into manufacturing cells and subsequently part families are assigned to cells. The problem encountered in CMS is construction of such cells regardless of its type (Selim et al., 1998). Not necessarily the abovementioned steps are conducted in the above order or even sequentially. Depending upon the procedures involved in CFP three methods of achieving solutions are demonstrated:

1 recognising part families first and consequently machines are clustered into cells depending on the processing requirement of part families

2 recognising manufacturing cells by grouping heterogeneous machines and then the part families are allocated to cells

3 part families and machine cells are developed concurrently.

Due to the NP-Complete nature of the problem (Unler and Gungor, 2009), many intelligent techniques are heavily practised to obtain improved solution to the CFP (Ghosh et al., 2010).

In present research, a new approach has been developed by exploiting median linkage clustering (MLC) technique hybridised with a part assignment heuristic algorithm. A brief survey of literature is presented in Section 2. The mathematical background of CFP is discussed in Section 3. The adopted methodology is elaborated in Section 4 and finally, to verify and establish the effectiveness of the proposed method computational results and discussion are presented in Section 5 and subsequent Section 6 is the conclusion of this study.

2 Literature review

Various techniques are developed to solve manufacturing CFPs since last 40 years, these include similarity coefficient methods, clustering analysis, array-based techniques, graph partitioning methods, etc. The similarity coefficient method in CMS was initiated by McAuley (1972). The similarity coefficient methodologies compute the resemblance between every couple of machines and thereafter cluster the machines into manufacturing cells based on the obtained similarity values. Few studies have proposed to measure dissimilarity value instead of similarity value for machine-part grouping problems. Dissimilarity coefficient was used for generalised CFP by considering the operation sequences and production volumes of parts (Prabhakaran et al., 2002). Most similarity coefficient methods utilised machine – part mapping chart. Few of them are single linkage clustering algorithm (McAuley, 1972), average linkage clustering algorithm (Seifoddini and Wolfe, 1986).

Clustering methods are categorised as hierarchical and non-hierarchical methods. Standard or typically designed clustering techniques could be utilised to build clusters of either components or machines. Machine – part grouping problem is based on production flow analysis, in which the machine-part production cells are formed by permuting rows and columns of the machine-part mapping chart in the form of a {0–1} incidence matrix. Some of the methods are rank order clustering (ROC) by King (1980), bond energy algorithm by McCornick et al. (1972), etc. Dimopoulos and Mort (2001) has proposed a hierarchical algorithm combined with genetic programming for CFP.

In array-based techniques the binary patterns (rows and columns) are extracted from the machine-part incidence matrix and the block diagonal cellular structure is reorganised. The ROC algorithm is one of the heavily exploited array-based techniques for CF (King, 1980). Considerable amendments and augmentations over ROC algorithm have been demonstrated by King and Nakornchai (1982), and Chandrasekharan and Rajagopalan (1986a). The direct clustering analysis (DCA) has been stated by Chan and Milner (1982), and bond energy analysis is performed further by McCornick et al. (1972).

In graph theory-based approach, the machines are projected as vertices and the resemblance between the pair of machines as the weights of the arcs. An ideal seed non-hierarchical clustering algorithm for cellular manufacturing is proposed by Chandrasekharan and Rajagopalan (1986a). Srinivasan (1994) stated a novel approach based on minimum spanning tree (MST) for the manufacturing CFP. A polynomial-time algorithm based on a graph theoretic approach was developed by Veeramani and Mani (1996) named as vertex-tree graphic matrices.

3 Mathematical formulation

The CFP in GT begins with two fundamental tasks, namely machine-CF and part-family identification. To form machine-cells similar machines are grouped and they are dedicated to manufacture one or more part-families. In part-family formation, parts with similar design features, attributes, shapes are grouped, with the aim to manufacture the group of parts within a cell. In general, the CFPs are represented in a matrix namely ‘machine-part incident matrix’, which contains elements, presented as either 0 or 1. Parts are arranged in columns and machines are in row in the incidence matrix. An example matrix is presented in Figure 1 (Waghodekar and Sahu, 1984). It depicts that machine1 processes part 1, 5, 6, 7, machine 2 processes part 2, 3, 4, 5, machine 3 processes part 3, 4, 5, 6, machine 4 processes part 1, 2, 3, 4 and machine 5 processes part 2, 4, 5, 6. In this matrix, a 0 indicates no mapping or no processing between machine-part and a 1 indicates mapping or processing between machine-part.

From Figure 1 solution matrix can be obtained after applying machine-part clustering technique to form block diagonal structure as square boxes (Figure 5). An ‘1’ outside the block means a part which processed through some machine which does not belong to the corresponding machine cell, i.e., bottleneck machine, therefore, the intercellular move cost will be added. This element is recognised as an exceptional element (EE) and a ‘0’ inside a cell means an unutilised space in cell, therefore, lesser utilisation of space and addition of intracellular move cost, is identified as ‘void’. The objective of CF is to minimise the EEs and voids.

Figure 1 Machine-part incidence matrix of example dataset (5 × 7)

	p1	p2	p3	p4	p5	p6	p7
m1	1				1	1	1
m2		1	1	1	1		
m3			1	1	1	1	
m4	1	1	1	1			
m5		1		1	1	1	

To formulate the CFP the followings are considered:

I set of m machines, $i = 1, \ldots, M$

J set of n parts, $j = 1,\ldots, P$.

The incidence matrix is $A = [a_{ij}]$ demonstrates,

$$a_{ij} = \begin{cases} 1 \; if \;\; part \; j \; goes \; through \; machine \; i \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{1}$$

To measure the goodness of solutions, different performance measures have been proposed by the researchers since past few decades. Various measures can be obtained from the critical survey of the performance measures (Sarker and Mondal, 1999). In this study grouping efficacy has been considered which is heavily utilised by other authors to measure the efficiency of obtained solutions (Kumar and Chandrasekharan, 1990) and it is given as,

$$\tau = \frac{E - E_e}{E + E_v} \tag{2}$$

where

E total number of 1s in matrix A

E_e total number of EEs

E_v total number of voids

The objective function which maximises the efficiency is as follows,

$$Maximise \; F = \frac{E_v + E_e}{E + E_v} \tag{3}$$

subject to

$$\sum_{k=1}^{K} x_{ik} = 1 \qquad i = 1, \ldots, M \tag{4}$$

$$\sum_{k=1}^{K} y_{jk} = 1 \qquad j = 1, \ldots, P \tag{5}$$

$$\sum_{k=1}^{K} x_{ik} \geq 1 \qquad k = 1, ..., K \tag{6}$$

$$\sum_{k=1}^{K} y_{jk} \geq 1 \qquad k = 1, ..., K \tag{7}$$

$$x_{ik} = 0 \ or \ 1 \qquad i = 1, ..., M; \ k = 1, ..., K \tag{8}$$

$$y_{jk} = 0 \ or \ 1 \qquad j = 1, ..., M; \ k = 1, ..., K \tag{9}$$

where

$$x_{ik} = \begin{cases} 1 \ if \ \ machine \ i \ is \ in \ cell \ k \\ 0 \qquad \qquad \qquad otherwise \end{cases} \tag{10}$$

(i = 1, …, M and k = 1, …, K) and

$$y_{ik} = \begin{cases} 1 \ if \ \ part \ j \ is \ in \ cell \ k \\ 0 \qquad \qquad otherwise \end{cases} \tag{11}$$

(j = 1, …, P and k = 1, …, K).

To evaluate the objective function F, it can be demonstrated,

$$E_e = E - \sum_{k=1}^{K} \sum_{i=1}^{M} \sum_{j=1}^{P} a_{ij} x_{ik} y_{jk} \tag{12}$$

$$E_v = \sum_{k=1}^{K} \sum_{i=1}^{M} \sum_{j=1}^{P} \left(1 - a_{ij}\right) x_{ik} y_{jk} \tag{13}$$

This objective function F is a fractional function in x and y. The constraints (4) and (5) depict that each machine and each part is assigned to exactly one cell, respectively. Further constraints (6) and (7) demonstrate each cell contains at least one machine and one part respectively. Binary variables are expressed in (8) and (9).

4 Solution methodology

The proposed methodology is based on Nei and Li's (1979) similarity coefficient method which is often known as Sorenson's similarity coefficient (Yin and Yasuda, 2005). The stated metric is combined with MLC technique to form the machine cell. MLC algorithm is adopted in this study as the machine CF technique which is theoretically and mathematically simple algorithm practiced in hierarchical clustering analysis of data (Anderberg, 1973). It delivers informative descriptions and visualisation of possible data clustering structures. When there exists hierarchical relationship in data this approach can be more competent. In this article, a hybrid approach is proposed which is further combined with a modified part assignment heuristic to facilitate efficient CF.

4.1 Similarity coefficient method

Similarity coefficient-based techniques are massively practiced in formation of manufacturing cells and a comprehensive study can be found in literature (Yin and Yasuda, 2005). In this article, the similarity measure method is utilised namely Nei and Li's (1979) similarity coefficient.

$$S_{ij} = \frac{2a_{ij}}{\left(a_{ij} + b_{ij}\right) + \left(a_{ij} + c_{ij}\right)} \tag{14}$$

S_{ij} similarity between machine i and machine j

a_{ij} the number of parts processed by both machines i and j

b_{ij} the number of parts processed by machine i but not by machine j

c_{ij} the number of parts processed by machine j but not by machine i.

Utilising the aforementioned similarity coefficient method similarity relationship can be obtained between machines and an $m \times m$ similarity matrix can be obtained as depicted in Figure 2.

Figure 2 Similarity matrix obtained of the example dataset (5 × 7)

	m1	m2	m3	m4	m5
m1	1				
m2	0.25	1			
m3	0.5	0.75	1		
m4	0.25	0.75	0.5	1	
m5	0.5	0.75	0.75	0.5	1

4.2 Machine group formation

The proposed hybrid technique exploits the similarity matrix obtained from the previous stage and produces dendrogram structure that links individual machines or subgroup of machines according to their values of similarity coefficients. Median linkage function is implemented on the basis of hierarchical cluster information. If machine cell r is formed combining cell p and q, x_{ri} is the ith machine of cell r, then median linkage is computed using the formula,

$$d(r,s) = \left\|\tilde{x}_r - \tilde{x}_s\right\|_2 \tag{15}$$

which is the Euclidean distance between the weighted centroids of two cells where,

$$\tilde{x}_r = \frac{1}{2}\left(\tilde{x}_p + \tilde{x}_q\right) \tag{16}$$

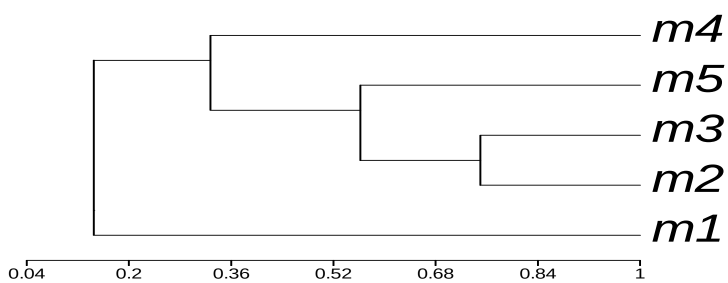
The matrix generated from this function is a $(m-1) \times 3$ matrix, where m is the number of machines in the original dataset. Columns of the matrix contain cluster indices linked in pairs to form a binary tree. The leaf nodes are numbered from *1* to m. Leaf nodes are the singleton clusters from which all higher clusters are built. Further, the dendrogram can be obtained from the matrix which indicates a tree of potential solutions. Therefore, it is a decision-maker's task to decide how to obtain a particular group of machines based on pre-selected similarity threshold.

Applying the median linkage procedure, the hierarchical information could be retrieved which is depicted in Figure 3. Further, the dendrogram is also obtained in Figure 4 which clearly depict the clustering information, i.e., cell 1 contains {machine 1} and cell 2 contains {machine 2, 3, 4, 5}.

Figure 3 Hierarchical relationships obtained e.g., dataset (5 × 7)

Node	Group 1	Group 2	Similarity
1	m2	m3	0.75
2	Node 1	m5	0.563
3	Node 2	m4	0.328
4	m1	Node 3	0.145

Figure 4 Dendrogram construction for the machine groups of the dataset (5 × 7)



4.3 Part assignment technique

In order to construct efficient part families, a novel technique is proposed in this study which is primarily inspired from the part grouping method proposed by Zolfaghari and Liang (2003) and modified substantially. This method is supportive to evaluate the CF structure obtained via the proposed hybrid method and to assign the part families to the cells according to their processing requirements. This phenomenon is based on identifying a machine cell which processes the part for a maximum number of operations than any other machine cell and assigning the corresponding part into that cell. Therefore, parts are assigned to the cells, which further form tangible part families using membership index given as,

$$D_{cj} = \frac{m_{cj}}{k_c} \times \frac{m_{cj}}{n_j} \times \frac{1}{v} \tag{17}$$

D_{cj} membership index of part *j* to cell *c*

m_{cj} number of machines in cell *c* which process part *j*

k_c total number of machines in cell *c*

n_j total number of machines required by part *j*

v total number of zeros (voids) in the cells in obtained block diagonal matrix.

In the above mathematical formula, the count of voids has been introduced, which implies the number of zeros in the cells. Using (s) the membership index value of each part can be computed. Larger the membership index value of a part for a particular cell, will subsequently assign it to that cell to obtain the final part families. The computed membership index is depicted in Table 1.

Table 1 Computing the membership index values for parts

Parts	*Membership index values*	
	Cell 1	*Cell 2*
P1	*0.167*	0.021
P2	0.167	*0.375*
P3	0	*0.375*
P4	0	*0.5*
P5	0.125	*0.187*
P6	*0.11*	0.066
P7	*0.5*	0

The above analysis illustrates the final CF. Part 1, 6, 7 are grouped into part family 1 and part 2, 3, 4, 5 are grouped into part family 2 and they are assigned to cell 1 and cell 2 respectively. Therefore, the final block diagonal structure is obtained with grouping efficacy value 69.56 (11% improved solution) and presented in Figure 5.

Figure 5 Final block diagonal CF of example dataset (5 × 7)

	p1	p7	p6	p4	p3	p5	p2
m1	1	1	1			1	
m2				1	1	1	1
m3			1	1	1	1	
m5			1	1		1	1
m4	1			1	1		1

4.4 Proposed hybrid algorithm

1 Procedure *Median_Linkage*

Step 1 compute similarity matrix using (14)

Step 2 construct dendrogram

Step 3 loop

Step 4 create machine cells for the highest level of similarity coefficient.

2 Procedure *part_assignment*

Step 1 find a machine cell that processes the part for a larger number of operations than any other machine cell

Step 2 find the ratio of number of machines which process that part and total number of machines required for that part to be processed

Step 3 find total number of voids in the cell configuration

Step 4 compute the membership index value using (17)

Step 5 assign the part to a cell for which the membership value is larger

Step 6 if tie occurs, opt the machine cell that has the largest number of machines visited by the part and assign it to that cell

Step 7 if further tie occurs; select the machine cell with the smallest identification number and assign the part in that machine cell.

3 Procedure *efficacy*

Step 1 calculate the fitness value of the cell configuration using (2)

Step 2 if solution is the best recorded so far, best = current solution

Step 3 else repeat procedure 1–3

Step 4 stop if no improvement found.

5 Performance metric

There are several performance metrics proposed by researchers in CMS domain. A detailed description regarding various performance measures could be obtained from a critical survey proposed by Sarker and Mondal (1999). Among these grouping efficiency and grouping efficacy are heavily practiced in past literature. Both the metrics are stated as,

5.1 Grouping efficiency (η)

Grouping efficiency is the very first performance measure in CFP. The higher grouping efficiency will result in better grouping (Chandrasekharan and Rajagopalan, 1986b). The metric was proposed as a weighted average of two efficiencies,

$$\eta = q \times \eta_1 + (1-q) \times \eta_2 \tag{18}$$

η_1 the ratio of the number of 1 s in the diagonal blocks to the total number of zeros and 1s in the diagonal block.

η_2 the ratio of the number of zeros in the off-diagonal blocks to the total number of elements in the off diagonal blocks.

q weight factor

5.2 Grouping efficacy (τ)

Grouping efficacy is a new performance measure, which has been proposed to overcome the drawbacks of grouping efficiency. High grouping efficacy will result as good CF (Kumar and Chandrasekharan, 1990),

$$\tau = \frac{E - E_e}{E + E_v} = 1 - \frac{E_v - E_e}{E + E_v} \tag{19}$$

where

E total number of 1 s in incidence matrix

E_e total number of EEs

E_v total number of voids

In order to verify the solutions obtained using the proposed technique, both the metrics are utilised in this article.

6 Computational result

The proposed method is tested with a set of 20 problems that have been published in the literature and have been widely used in many comparative studies. All the datasets were transcribed from the original articles to avoid the inconsistency in data. The proposed method is simulated with multivariate statistical analysis toolbox and MATLAB 7.0 and tested on a laptop with a 2.1 GHz processor and 2GB of RAM. Comparisons of the proposed method against other algorithms from the literature are given in Table 2. These algorithms include ZODIAC (Chandrasekharan and Rajagopalan. 1987), GRAFICS (Srinivasan and Narendran, 1991), GATSP-genetic slgorithm (Cheng et al., 1998), GA-genetic algorithm (Onwubolu and Mutingi, 2001), MST (Srinivasan, 1994), GP (Dimopoulos and Mort, 2001). This comparison is performed based on the grouping efficacy value obtained using the proposed method. For the problems solved with the proposed method to obtain optimal solution, the grouping efficacy value is better or equal in all instances. In order to demonstrate the superiority of the proposed technique, furthermore the results are verified with grouping efficiency measure. This comparison is performed against the results obtained using GRAFICS (Srinivasan and Narendran, 1991) and Viswanathan's algorithm (1996). The observations indicate that the proposed hierarchical clustering technique is efficient and less complex because of its simplicity in simulation. All the solutions are obtained with negligible computational time (< 5 CPU seconds). Therefore, this technique is highly comparable with complex soft computing techniques such as genetic algorithms, evolutionary techniques, GA-TSP, etc. The above technique is shown to outperform the standard techniques in 12 instances, equal in 8 instances based on grouping efficacy measure (Table 2) and also outpace the GRAFICS as well as Viswanathan's algorithm in 7 instances, equal in 4 instances (Table 3).

Table 2 Computational results in terms of grouping efficacy

#	*Dataset references*	*size*	*ZODIAC*	*GRAFICS*	*GA-TSP*	*GA*	*GP*	*MST*	*hybrid*
1	K&N (1982)	5 × 7	73.68	73.68					73.68
2	W&S (1984)	5 × 7	56.52	60.87					*69.56**
3	Seifoddini (1989)	5 × 18			77.36	77.36			*79.59*
4	K&C (1992)	6 × 8			76.92	76.92			76.92
5	K&C1 (1987)	7 × 11	39.13	53.12	46.88	50			*59.26*
6	Boctor (1991)	7 × 11			70.37	70.37			70.37
7	S&W (1986)	8 × 12	68.3	68.3					68.3
8	C&R (1986a)	8 × 20	58.33	58.13	58.33	55.91	58.7	58.72	58.72
9	C&R (1986b)	8 × 20	85.24	85.24	85.24	85.24	85.2	85.24	*86.67*
10	C&M (1982)	10 × 15	92	92	92	92	92		92
11	A&S (1987)	14 × 24	64.36	64.36				64.36	*66.2*
12	Stanfel (1985)	14 × 24	65.55	65.55	67.44	63.48	63.5		*69.33*
13	Sr (1990)	16 × 30	67.83	67.83				67.83	*68.5*
14	M&T (1985)	20 × 20	21.63	38.26	37.12	34.16			*39.23*
15	Carrie (1973)	20 × 35	75.14	75.14	75.28	66.3	76.7	75.14	*75.9*
16	C&R (1989)-1	24 × 40	100	100	100	100	100	100	100
17	C&R (1989)-2	24 × 40	85.1	85.1	85.11	85.11	85.1	85.11	85.11
18	Stanfel (1985)-1	30 × 50	46.06	56.32	56.61	48.28	59.4	58.7	*60.12*
19	Stanfel (1985)-2	30 × 50	21.11	47.96	45.93	37.55	50	46.3	*59.53*
20	C&R (1987)	40 × 100	83.92	83.92	84.03	83.9	84	83.66	*84.15*

Notes: *Improved results are shown in boldface; C&R – Chandrasekharan and Rajagopalan; K&N-King and Nakornchai; W&S – Waghodekar and Sahu; K&C – Kusiak and Cho; K&C1 – Kusiak and Chow; S&W – Seifoddini and Wolfe; C&M – Chan and Milner; A&S – Askin and Subramanian; Sr – Srinivasan et al.; M&T – Mosier and Taube

Figure 6 and Figure 7 present the comparison among the proposed method with published techniques, which further depicts 60% and 63.63% improved results respectively which are significant in terms of solution superiorities and time and space complexities. The managerial implications of the proposed method would be in practicing simple but efficient methodology in CMS to achieve more efficient cells and robust part families by maximising the grouping efficacy. Thus, it reduces the overall intracell and intercell material flow and thereafter it reduces the total production cost.

Table 3 Computational results in terms of grouping efficiency

#	*Datasets*	*Size*	*GRAFICS*	*Viswanathan's algorithm*	*Hybrid*
1	King and Nakornchai (1982)	5 × 7	85.62	85.62	85.62
2	Waghodekar and Sahu (1984)	5 × 7	74.51	78.57	*85.15**
3	Kusiak and Chow (1987)	7 × 11	76.81	70.95	*85.69*
4	Seifoddini and Wolfe (1986)	8 × 12	87.11	85.53	87.11
5	C&R (1986a)	8 × 20	95.83	95.83	*97.44*
6	C&R (1986b)	8 × 20	76.3	71.88	*77.07*
7	Askin and Subramanian (1987)	14 × 24	82.54	82.16	*84.9*
8	Srinivasan et al. (1990)	16 × 30	86.44	85.56	*87.29*
9	C&R (1989)-1	24 × 40	100	100	100
10	C&R (1989)-2	24 × 40	95.2	95.2	95.2
11	C&R (1987)	40 × 100	95.07	95.12	*95.33*

Notes: *Improved results are shown in boldface; C&R – Chandrasekharan and Rajagopalan.

Figure 6 Improvement curve of the proposed hybrid technique based on grouping efficacy (see online version for colours)

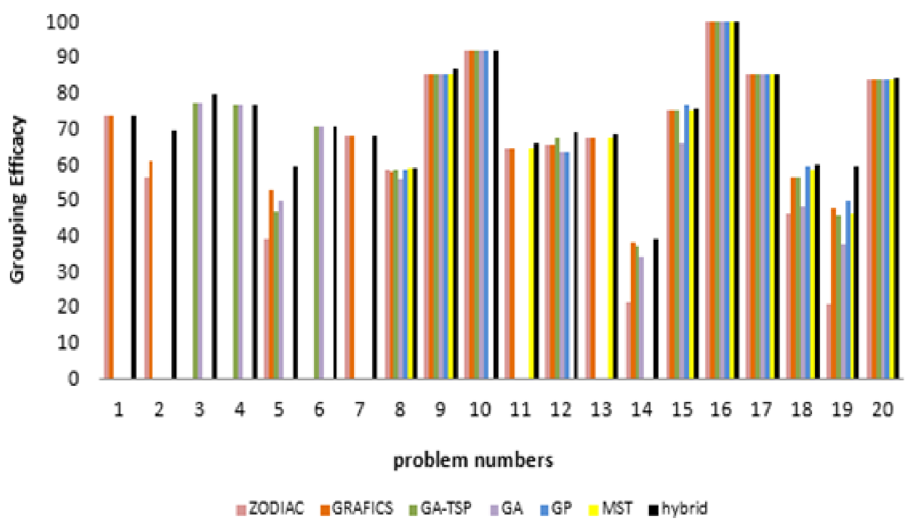
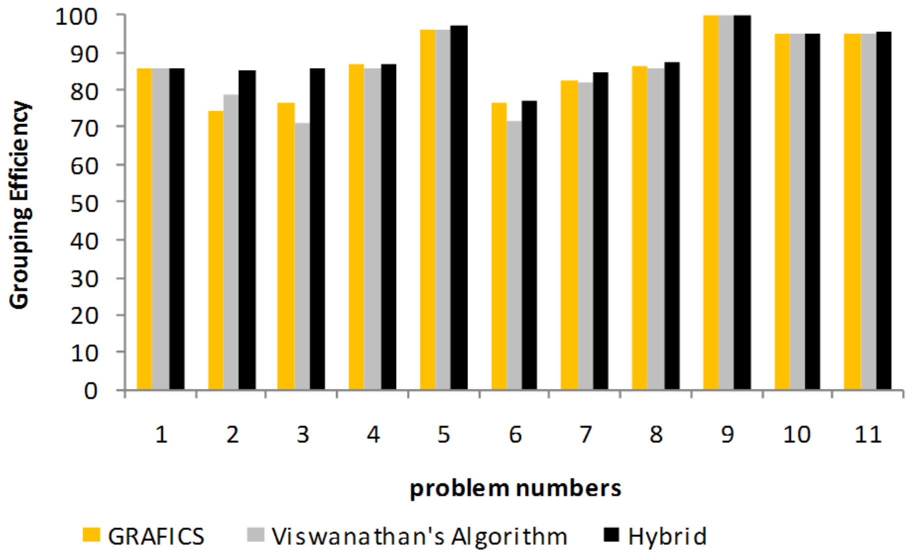


Figure 7 Improvement curve of the proposed hybrid technique based on grouping efficiency (see online version for colours)



7 Conclusions

This study demonstrates a hybrid clustering technique that combines Nei and Li's (1979) similarity coefficient method and hierarchical MLC technique. Inclusion of Nei and Li's similarity index into a standard hierarchical clustering technique can improve the solution quality eventually and inclusion of efficient part grouping heuristic can increase the computation speed. Computational results presented in Section 6 demonstrate that the hybrid technique outperforms not only the standard clustering techniques, but also several other well-known soft computing-based CF solution methodologies such as genetic algorithms and GA-TSP from the literature. Therefore, the proposed method obtains improved solutions by consuming lesser computational time and resources than that of the traditional complex soft computing-based methodologies. It is also shown that the hybrid technique performs at least as well as and often better than some of the best algorithms for the CF on all test problems.

Acknowledgements

The authors are grateful to the anonymous reviewers for their valuable comments and suggestions.

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